A NEW EDGE DETECTION METHOD TO FIND THE REGION OF INTEREST IN SA ECHOCARDIOGRAPHIC IMAGES

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***Abstract*- Determining the initial curve in a deformable model segmentation method is of great importance. This problem is more severe in Ultrasound images because of the speckle noise contaminating it. In this paper, we proposed a fuzzy wavelet-based edge detection method to find edges in noisy images. We used the new method to determine region of interest in echocardiographical images. Usefulness and potentials of the proposed algorithm is demonstrated by successfully applying it to different noisy images and reducing the number of iterations of the deformable model based segmentation method.**

***Key words*-Wavelet Transform, SA view, Speckle noise, Echocardiography images.**

I. Introduction

Identifying the heart chambers, the endocardium, and the epicardium is a powerful diagnostic tool. Among heart chambers, the detection, segmentation and tracking of the left ventricle are of great importance. This heart chamber pumps the oxygenated blood out to distant tissue in the entire body. By measuring the ventricular blood volume, wall mass, wall motion, and the wall thickening of left ventricle, a variety of heart diseases will be diagnosed.

One of the techniques for studying heart is echocardiography that is the Ultrasonic Imaging of the living heart. Echocardiography is a real-time, noninvasive, nonradioactive and inexpensive imaging method. The real-time capability of echocardiography lends itself very well to the examination of the heart, where the motion of structures is frequently of utmost concern. Also in comparison to other techniques such as Magnetic Resonance Imaging (MRI) and Computerized Tomography (CT), the instrumentation of ultrasonic imaging is relatively simple and portable instruments are available.

After data acquisition, the first step of evaluating the parameters of left ventricle, quantitatively and subjectively, is contour extraction. Several segmentation methods meet this requirement. Because of diagnostic consideration and huge volume of data, desirable methods should be precise and automatic.

An overview of segmentation methods for echocardiographic data can be found in [1]. Also a number of issues concerning the development of techniques and algorithms for the automation of the boundary extraction process using variety of imaging techniques are reported in [2-4]. More recent notable solutions for segmentation of two-dimensional (2D) echocardiographic images have involved statistical shape models [5] and active appearance models [6]. Mishra et al. [7] proposed a Genetic Algorithm (GA) based method for boundary detection of left ventricle. They formulated the contour detection algorithm as a constrained optimization problem based on active contour model and solved the optimization problem using GA. Zagrodsky et al. [8] reported a two stage segmentation method. In the first stage, the initialization stage, mutual-information registration of a voxel template with the image to be segmented helps initialize a wiremesh template. Then, in the second stage, the refinement stage, the wiremesh is refined iteratively under the influence of external and internal forces.

A different group of methods in this field are edge-detection methods. An overview of these methods is found in [9-11]. Sun et al. [12] proposed a multi-scale edge detection algorithm based on wavelet domain vector hidden Markov tree model (WD-VHMT). They employed the WD-VHMT to model the statistical properties of multi-scale and multidirectional wavelet coefficients of an image. Then this model is trained by an expectation maximization algorithm. After that, an extended Viterbi algorithm is employed to uncover the hidden state sequences and reveal the edges. Yu et al. [13] reported an Edge Detection method in ultrasonic imagery using the instantaneous coefficients of variations (ICOV). In this method edge localization is characterized by the peak and the 3-dB width of the ICOV detector response.

Applying segmentation methods to Ultrasound Images is not straightforward because of low signal-to-noise ratio (SNR), low contrast between tissues and a special kind of noise called speckle. Speckle is a dominating disturbance in ultrasound images. This noise causes ultrasound images look so grainy. On the other hand, almost, all above mentioned segmentation methods need gradient, laplacian or generally differential quantities of the image to be calculated that existence of speckle spoils calculation of them. Also, speckle causes the tuning of parameters of segmentation methods (especially those based on deformable models) to be hard and causes these methods to be too dependent to initial conditions. For this reason, we aim to avoid differential quantities in our methods or reduce the calculation of these quantities leastwise (by decreasing the iterations e. g.).

In this paper, we firstly introduce our new method of edge detection in noisy cases and then we apply it to SA view echocardiography images to find the region of interest for initialization of deformable model segmentation methods.

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The remainder of this paper is organized as follows. In section II, materials are introduced. The new edge detection method is proposed in section III. Section V is Result section and Conclusion is the section VI.

II. MATERIAL AND METHODS

The echocardiographic images used in this study are typical SA echocardiographic images obtained from different subjects and in different instants of cardiac cycle in the Cardiology Department of the Western Infirmary in Glasgow. The images were generated on a HP Ultrasound system which was operating at 3MHz and 3.5MHz. Fig. 1 shows a typical example image from the image data base.

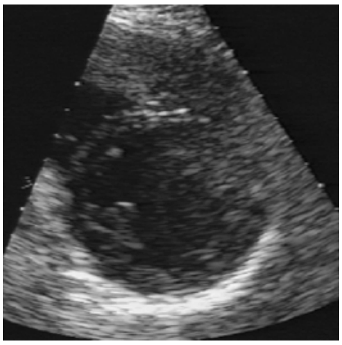

Fig. 1. Typical SA echo image from data base.

IV. PROPOSED METHOD

A. EDGE DETECTION PROPERTY OF WAVELET TRANSFORM

Finding edge in noisy signal or image is difficult. Using first-order or second-order derivatives with high-pass characteristic for edge detection makes the signal or image noisier and hence makes the edges to be disappeared. One way to take advantage of these operators in noisy case is to smooth the signal or image in advance in order to reduce the noise.

In general, the larger the size of the smoothing operator the clearer the edge appears but at the expense of reduction in the localization precision. Canny [14] showed that there is a natural uncertainty principle between detection and localization performances of the edge operators, in general, in finding noisy edges. So it is better to use a multi-scale method in order to have a trade-off between detection and localization and find the best case. By multi-scale, we mean to change the size of smoothing so bring it into different scales.

One of multi-scale techniques is Wavelet Transform (WT). The WT of a 1-D real function $f(x)$ with respect to a mother wavelet $\psi(x)$ is represented as:

$$W_\psi f(s,t) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} f(x) \psi\left(\frac{x-t}{s}\right) dx \qquad (1)$$

Equation (1) is interpreted as a convolution product:

$$W_\psi f(s,t) = f(t) * \psi_s(t) \qquad (2)$$

Where:

$$\psi_s(x) = \frac{1}{\sqrt{s}} \psi\left(\frac{x}{s}\right) \qquad (3)$$

Now if we assume the mother wavelet is chosen so that $\psi(x) = \frac{d\varphi(x)}{dx}$ in which $\varphi(x)$ is a smoothing function having the following property:

$$\int_{-\infty}^{+\infty} \varphi(x)\, dx = 1 \qquad (4)$$

Then we would have a multi-scale edge detector:

$$\begin{aligned} W_\psi f(s,t) &= f(t) * \psi_s(t) = f(x) * \left(-s \frac{d\varphi_s(-t)}{dt}\right) = \\ &-s\left(f(t) * \frac{d\varphi_s(-t)}{dt}\right) = s\frac{d}{dt}\big(f(t) * \varphi_s(t)\big) \end{aligned} \qquad (5)$$

B. FUZZY WAVELET-BASED EDGE DETECTION METHOD

Because of ambiguity in edge detection and localization confined to each scale at wavelet decomposition levels, it is better to combine information in the different wavelet scales together. Fuzzy logic set theory and operators which gained popularity in modeling and propagating ambiguity in signal and image processing over the past few years, help us to do so and decide for the edges.

In this study a special 2-D discrete wavelet decomposition proposed in [15], was used. Major difference of this method from typical DWT2 is that the down-sampling stage is eliminated to have a shift-invariant wavelet transform. Also, it has two detailed sub-bands instead of three which show the horizontal and vertical details of an image. Stages of our edge detection method are illustrated in Fig. 2.

Assuming that the decomposition is done up to J level and each sub-band has N points; each point in wavelet domain is labeled as below:

$$W_\psi f(j,k): \quad k = 1,2,...,N \quad j = 1,2,....,J \qquad (6)$$

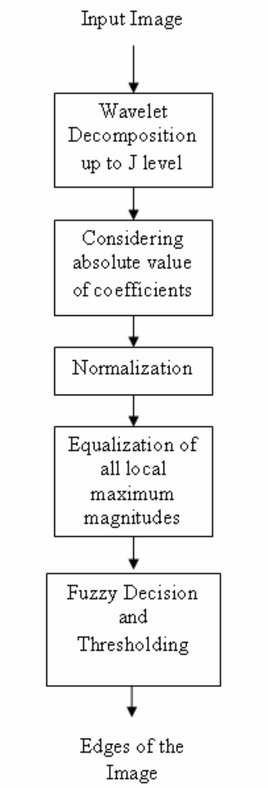

Fig. 2. Block diagram of our fuzzy edge detection method.

Rising edges cause significant positive values and falling edges cause significant negative values in detailed sub-bands while values due to noise oscillate around zero. Hence, to process the two kinds of edges simultaneously, the absolute value of each coefficient is considered. The first operator $F_1(\cdot)$ is defined as follow:

$$S_{1j}(k) = F_1\big(W_\psi f(j,k)\big) = abs\big(W_\psi f(j,k)\big) \quad (7)$$

Next, each $S_{1j}(k)$ is normalized to have a maximum value of unity because the valuation set of a fuzzy set is the real interval $[0,1]$. So we have:

$$S_{2j}(k) = F_2\big(S_{1j}(k)\big) = \frac{S_{1j}(k)}{\max_{k=1}^{N} S_{1j}(k)} \quad (8)$$

Since any given local maximum at any scale is a representative of a positive or negative transition in the image, which could be an edge, it is logical to assign an equal membership value of unity to all local maxima at each scale. The operator $F_3(\cdot)$ produces the final multi-scale edge fuzzy subsets $S_{3j}(k)$ as follows:

$$S_{3j}(k) = F_3\big(S_{2j}(k)\big) = \begin{cases} 1 & \text{if } S_{2j}(k) \text{ is local maximum} \\ S_{2j}(k) & \text{else} \end{cases} \quad (9)$$

Any fuzzy set $S_{3j}(k)$, denotes the grade of possessing the same property of 'edginess' with different scale information at any point k. So the logical way to combine their information is to find the fuzzy intersection of fuzzy sets. In our procedure we ignore the information provided by the first scale because this scale is dominated by the noise. The intersection fuzzy set $S_E(k)$ is then defined as:

$$S_E(k) = \min_{2 \le j \le J}\big(S_{3j}(k)\big) \quad (10)$$

At the end of procedure, edges would be appeared by defining a threshold for $S_E(k)$. We combine the result of edge detection in horizontal and vertical sub-bands to have a continuous edge.

V. Results

Initially, a sample image shown in Figure 3 is used to demonstrate the effectiveness of the proposed algorithm. The sample image is contaminated by speckle and Gaussian noise with different variances varying from 0.01 to 0.1. The results are shown in Fig. 7.

It can be seen that, the proposed method could find the edges in all noisy images. What is worth mentioning is that as the variance of noise increases, the edges become wider and more discontinuous. In this case additional simple processing is needed to have a perfect edge.

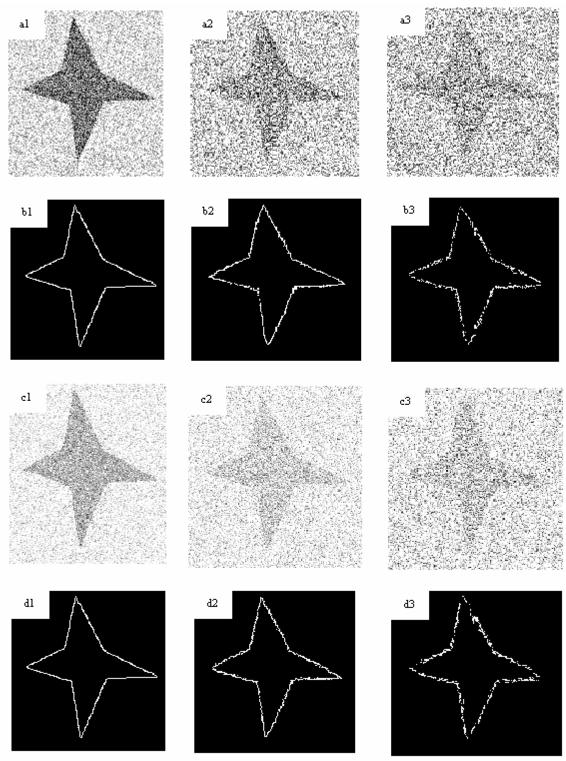

Fig. 3. (a1-a3) Star image contaminated by speckle noise with variances 0.01, 0.05 and 0.1 respectively. (b1-b3) Detected edges of images a1-a3. (c1-c3) Star image contaminated by Gaussian zero-mean noise with variances 0.01, 0.05 and 0.1 respectively. (d1-d3) Detected edges of images c1-c3.

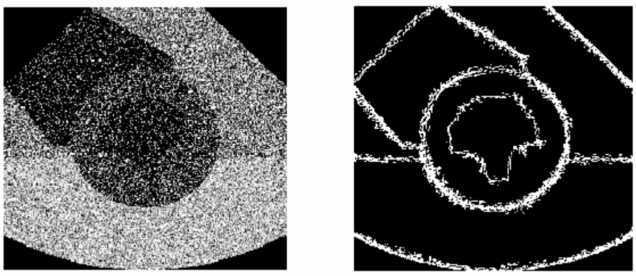

Fig. 4. Simulated image of heart (left) and detected edges by the proposed method (right).

A simulated echocardiographic image is then used to assess the effectiveness of the algorithm. The image made of various amount of speckle noise mimicking various tissues. The simulated image and the result are shown in Fig. 4.

Finally, the proposed algorithm is applied to real echocardiography images. The results of application to three different SA images are shown in Fig. 5. As it can be seen, for the real images, the algorithm lacks to find continuous edges like the one found in the simulated image. However, the extracted discontinuous edges in the real images can be used for automatically locating an initial border to be used with the deformable model methods.

Our strategy is to apply the edge detection method to the image and then determine the threshold such a way that strong edges (border of blood and myocardium) remain. Then by applying morphological operation 'closing' we obtain monolith parts. To eliminate remaining unrelated points which are stationary related to walls, we take advantage of neighbor frames.

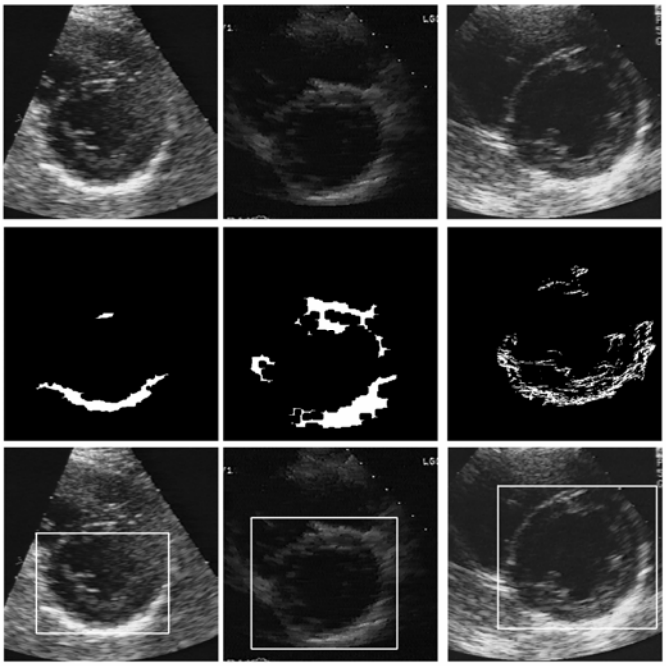

Fig. 5. Top: different SA view echocardiography images. Middle: result of application our method. Bottom: resulted region of interests.

VI. CONCLUSION

In this paper, we have proposed a wavelet based edge detection method to find edges in noisy images. The method was applied to star image with Gaussian and speckle noise of different variance ranging from 0.01 to 0.1 and also simulated echocardiograph image and found continuous edges. Region of Interest in SA echocardiographic images was found by this method, automatically which is useful for the initialization of deformable model methods.

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